Probability in High Dimensions

Solutions to Exercises, Week 6

August 30, 2020

3.1 Subgaussian variables and Chernoff bounds

Problem 3.1 (Subgaussian variables). There are several different notions of random variables with a Gaussian tail that are all essentially equivalent up to constants. The aim of this problem is to obtain some insight into these notions.

- a. As a warmup exercise, show that if X is σ^2 -subgaussian, then $\operatorname{Var} X \leq \sigma^2$.
- b. Show that for any increasing and differentiable function Φ

$$\mathbf{E}\,\Phi(|X|) = \Phi(0) + \int_0^\infty \Phi'(t)\,\mathbf{P}[|X| \ge t]\,dt$$

- c. In the following five parts, assume for simplicity that $\mathbf{E} X = 0$. Show that if X is σ^2 -subgaussian, then $\mathbf{P}[|X| \ge t] \le 2e^{-t^2/2\sigma^2}$.
- d. Show that if $\mathbf{P}[|X| \ge t] \le 2e^{-t^2/2\sigma^2}$, then $\mathbf{E}[e^{X^2/6\sigma^2}] \le 2$.
- e. Show that if $\mathbf{E}[e^{X^2/6\sigma^2}] \leq 2$, then X is $18\sigma^2$ -subgaussian
- f. Show that if X is σ^2 -subgaussian, then $\mathbf{E}[X^{2q}] \leq (4\sigma^2)^q q!$ for all $q \in \mathbb{N}$.
- g. Show that if $\mathbf{E}[X^{2q}] \leq (4\sigma^2)^q q!$ for all $q \in \mathbb{N}$, then $\mathbf{E}\left[e^{X^2/8\sigma^2}\right] \leq 2$.
- Solution. a. First note that $\psi(0) = \psi'(0) = 0$ for all random variables X, and $\psi''(0) = \operatorname{Var} X$ follows from the expression for $\psi''(\lambda)$ given in the proof of Lemma 3.6. Hence $\psi(\lambda) = \frac{1}{2}\lambda^2 \operatorname{Var} X + o(\lambda^2)$ and so it follows from the definition of subgaussian that $\operatorname{Var} X \leq \sigma^2$.
 - b. For simplicity assume $X \ge 0$ almost surely. By the Fundamental Theorem of Calculus,

$$\Phi(x) = \Phi(0) + \int_0^x \Phi'(t) dt = \Phi(0) + \int_0^\infty \mathbf{I}_{\{t \le x\}} \Phi'(t) dt$$

so
$$\mathbf{E} \Phi(X) = \Phi(0) + \mathbf{E} \int_0^\infty \mathbf{I}_{\{X \ge t\}} \Phi'(t) dt$$
$$= \Phi(0) + \int_0^\infty \Phi'(t) \mathbf{E} \mathbf{I}_{\{X \ge t\}} dt$$

by Fubini's/Tonelli's Theorem (the integrand is non-negative by the conditions given), giving the result.

c. Since $\mathbf{E} X = 0$, we can apply the Chernoff bound to both the upper and lower tails to obtain

$$\mathbf{P}[X \ge t] \le e^{-t^2/2\sigma^2}$$
 and $\mathbf{P}[X \le -t] \le e^{-t^2/2\sigma^2}$

For the second bound, we have that $\mathbf{P}[X \leq -t] = \mathbf{P}[-X \geq t]$. Now, we can sum the above inequalities to obtain

$$\mathbf{P}[|X| \ge t] = \mathbf{P}[X \ge t] + \mathbf{P}[-X \ge t] \le 2e^{-t^2/2\sigma}$$

since $t \ge 0$.

d. Take $\Phi(t) = e^{t^2/6\sigma^2}$, which is differentiable and increasing on \mathbb{R}^+ . Then by b we have

$$\begin{split} \mathbf{E} \, \Phi(|X|) &= 1 + \frac{1}{3\sigma^2} \int_0^\infty t e^{t^2/6\sigma^2} \, \mathbf{P}[|X| \ge t] \, dt \\ \mathbf{E} \, e^{X^2/6\sigma^2} \le 1 + \frac{1}{3\sigma^2} \int_0^\infty t e^{t^2/6\sigma^2} 2e^{-t^2/2\sigma^2} \, dt \\ &= 1 + \frac{2}{3\sigma^2} \int_0^\infty t e^{-t^2/3\sigma^2} \, dt \\ &= 1 + 1 = 2. \end{split}$$

e. Recall that we assume $\mathbf{E}[X] = 0$. We have for any λ ,

$$\begin{split} \mathbf{E}[e^{\lambda X}] &= \mathbf{E}[\sum_{k \ge 0} \frac{(\lambda X)^k}{k!}] \\ &= 1 + \frac{\lambda^2}{2} \, \mathbf{E}[X^2 \sum_{k \ge 2} 2 \frac{(\lambda X)^{k-2}}{k!}] \\ &\leq 1 + \frac{\lambda^2}{2} \, \mathbf{E}[X^2 \sum_{k \ge 0} \frac{(|\lambda X|)^k}{k!} \frac{2}{(k+1)(k+2)}] \\ &\leq 1 + \frac{\lambda^2}{2} \, \mathbf{E}[X^2 \sum_{k \ge 0} \frac{(|\lambda X|)^k}{k!}] \\ &= 1 + \frac{\lambda^2}{2} \, \mathbf{E}[X^2 e^{|\lambda X|}] \end{split}$$

Let c > 0. Using Young's inequality we have,

$$|\lambda X| \le \frac{c\lambda^2}{2} + \frac{X^2}{2c}$$

Therefore,

$$\begin{aligned} \mathbf{E}[e^{\lambda X}] &\leq 1 + \frac{\lambda^2}{2} e^{\frac{c\lambda^2}{2}} \mathbf{E}[X^2 e^{\frac{X^2}{2c}}] \\ &\leq 1 + \frac{c\lambda^2}{2} e^{\frac{c\lambda^2}{2}} \mathbf{E}[e^{\frac{X^2}{c}}] \quad \text{(using the fact that } 2\frac{X^2}{2c} \leq e^{\frac{X^2}{2c}}) \\ &\leq 1 + c\lambda^2 e^{\frac{c\lambda^2}{2}} \quad \text{(by choosing } c = 6\sigma^2) \end{aligned}$$

Now we use the following Lemma.

Lemma 1. For $x \ge 0$, we have :

$$1 + 2xe^x \le e^{2x}$$

Proof. It is sufficient to show the inequality between the coefficients in the series expansion of both sides. For the left-hand side, the coefficient of x^k is $\frac{2}{(k-1)!}$, and for the right-hand expression, the coefficient of x^k is $\frac{2^k}{k!}$. So the inequality is equivalent to having for any $k \ge 1$:

$$\frac{2}{(k-1)!} \le \frac{2^k}{k!}$$
$$\iff 2k \le 2^k$$
$$\iff k \le 2^{k-1}$$

which is true for any $k \ge 1$.

Using this we now have,

$$\mathbf{E}[e^{\lambda X}] \le 1 + c\lambda^2 e^{\frac{c\lambda^2}{2}}$$
$$\le e^{\frac{2c\lambda^2}{2}}$$
$$= e^{\frac{12\sigma^2\lambda^2}{2}}$$

We conclude that X is $12\sigma^2$ -subgaussian and thus $18\sigma^2$ -subgaussian.

f. Let $\Phi(x) = x^{2q}$ for $q \in \mathbb{N}$. Then $\Phi'(x) = 2qx^{2q-1}$. Since Φ is differentiable and increasing, we will use part (b), i.e.

$$\begin{split} \mathbf{E}[X^{2q}] &= \Phi(0) + \int_0^\infty 2qt^{2q-1} \, \mathbf{P}(|X| \ge t) dt \\ &\le 4q \int_0^\infty t^{2q-1} e^{-t^2/2\sigma^2} dt. \end{split}$$

Now, performing the change of variable $u = \frac{t^2}{2\sigma^2}$, we can rewrite the inequality as

$$\begin{split} \mathbf{E}[X^{2q}] &\leq 4q \int_0^\infty (2\sigma^2 u)^{q-1} e^{-u} \sigma^2 du \\ &= 2^{q+1} \sigma^{2q} \int_0^\infty u^{q-1} e^{-u} du \\ &= 2^{q+1} \sigma^{2q} q! \\ &\leq (4\sigma^2)^q q!, \end{split}$$

where the second last line holds from the definition of the gamma function evaluated at a natural number.

g. We can prove this directly by expanding $\mathbf{E}\left[e^{X^2/8\sigma^2}\right]$ as a power series:

$$\begin{split} \mathbf{E}\left[e^{X^2/8\sigma^2}\right] &= \sum_{q=0}^{\infty} \frac{\mathbf{E}[X^{2q}]}{8^q \sigma^{2q} q!} \\ &\leq \sum_{q=0}^{\infty} \frac{(4\sigma^2)^q q!}{8^q \sigma^{2q} q!} \\ &= \sum_{q=0}^{\infty} 2^{-q} = 2. \end{split}$$

Problem 3.2 (Tightness of Hoeffding's Lemma). Show that the bound of Hoeffding's lemma is the best possible by considering $P(X = a) = P(X = b) = \frac{1}{2}$.

Solution. The distribution suggested has variance $(b-a)^2/4$, so the tightness follows from Problem 3.1a.

Problem 3.3 (Chernoff bound vs. moments). Show that for $t \ge 0$,

$$\mathbf{P}[X - \mathbf{E} X \ge t] \le \inf_{p \ge 0} \frac{\mathbf{E} \left[(X - \mathbf{E} X)_+^p \right]}{t^p} \le \inf_{\lambda \ge 0} e^{-\lambda t} \mathbf{E} \left[e^{\lambda (X - \mathbf{E} X)} \right].$$

Solution. We can see that, for any $\lambda \geq 0$,

$$\begin{split} \mathbf{E} \left[e^{\lambda(X - \mathbf{E} X)} \right] &\geq \mathbf{E} \left[\mathbf{1}_{X - \mathbf{E} X > 0} \ e^{\lambda(X - \mathbf{E} X)} \right] \\ &= \mathbf{E} \left[\mathbf{1}_{X - \mathbf{E} X > 0} \ \sum_{p=0}^{\infty} \frac{\lambda^p (X - \mathbf{E} X)^p}{p!} \right] \\ &= \mathbf{E} \left[\sum_{p=0}^{\infty} \frac{\lambda^p (X - \mathbf{E} X)_+^p}{p!} \right] \\ &= \sum_{p=0}^{\infty} \frac{\lambda^p \mathbf{E} \left[(X - \mathbf{E} X)_+^p \right]}{p!}, \end{split}$$

where the final line follows since the terms $(X - \mathbf{E} X)^p_+$ are non-negative for all $p \ge 0$. Therefore, we have

$$\begin{split} e^{-\lambda t} \mathbf{E} \left[e^{\lambda (X - \mathbf{E} X)} \right] &\geq \left(\sum_{p=0}^{\infty} \frac{\lambda^p \mathbf{E} \left[(X - \mathbf{E} X)_+^p \right]}{p!} \right) \Big/ \left(\sum_{p=0}^{\infty} \frac{\lambda^p t^p}{p!} \right) \\ &\geq \inf_{p \geq 0} \left\{ \frac{\lambda^p \mathbf{E} \left[(X - \mathbf{E} X)_+^p \right]}{p!} \Big/ \frac{\lambda^p t^p}{p!} \right\} \\ &= \inf_{p \geq 0} \frac{\mathbf{E} \left[(X - \mathbf{E} X)_+^p \right]}{t^p}, \end{split}$$

where the second inequality follows since the terms in both sums are all non-negative and the sums converge. Since the right-hand side of our final result is independent of λ , we could optimize the left-hand side with respect to λ to obtain the final result. Solution (alternative). Starts similarly to the previous one, but the end is different. For any $\lambda \ge 0$,

$$\begin{split} \mathbf{E}[e^{\lambda(X-\mathbf{E}[X])}] &\geq \mathbf{E} \left[\mathbf{1}_{X-\mathbf{E}[X]>0} \ e^{\lambda(X-\mathbf{E}[X])} \right] \\ &= \mathbf{E} \left[\mathbf{1}_{X-\mathbf{E}[X]>0} \ \sum_{p=0}^{\infty} \frac{(\lambda(X-\mathbf{E}[X]))^p}{p!} \right] \\ &= \sum_{p=0}^{\infty} \frac{\lambda^p}{p!} \mathbf{E} \left[\mathbf{1}_{X-\mathbf{E}[X]>0} \ (X-\mathbf{E}[X])^p \right] \\ &= \sum_{p=0}^{\infty} \frac{(\lambda t)^p}{p!} \frac{\mathbf{E} \left[(X-\mathbf{E}[X])_+^p \right]}{t^p} \\ &\geq \sum_{p=0}^{\infty} \frac{(\lambda t)^p}{p!} \inf_{p\geq 0} \frac{\mathbf{E} \left[(X-\mathbf{E}[X])_+^p \right]}{t^p}. \end{split}$$

Therefore,

$$e^{-\lambda t} \mathbf{E}[e^{\lambda(X-\mathbf{E}[X])}] \ge \inf_{p\ge 0} \frac{\mathbf{E}\left[(X-\mathbf{E}[X])_+^p\right]}{t^p},$$

which yields the result given that the inequality holds for all $\lambda \ge 0$. Remark: We should consider t > 0.

Problem 3.4.

Problem 3.5 (Maxima of subgaussian variables). Let X_1, X_2, \ldots be (not necessarily independent) σ^2 -subgaussian random variables. Show that

$$\mathbf{P}\left[\max_{i\leq n} \{X_i - \mathbf{E}[X_i]\} \ge (1+\epsilon)\sigma\sqrt{2\log n}\right] \xrightarrow{n\to\infty} 0 \quad \text{for all } \epsilon > 0.$$

Solution. We have

$$\mathbf{P}\left[\max_{i\leq n} \{X_i - \mathbf{E}[X_i]\} \ge (1+\epsilon)\sigma\sqrt{2\log n}\right] = \mathbf{P}\left[\bigcup_{i=1}^n \{X_i - \mathbf{E}[X_i] \ge (1+\epsilon)\sigma\sqrt{2\log n}\}\right]$$
$$\leq \sum_{i=1}^n \mathbf{P}\left[X_i - \mathbf{E}[X_i] \ge (1+\epsilon)\sigma\sqrt{2\log n}\right]$$
$$\leq \sum_{i=1}^n 2\exp\left\{-\left((1+\epsilon)\sigma\sqrt{2\log n}\right)^2 \middle/ (2\sigma^2)\right\}$$
$$= 2n\frac{1}{n^{(1+\epsilon)^2}} \xrightarrow{n\to\infty} 0,$$

for all $\epsilon > 0$.